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BIOMORPHIC NETWORKS FOR ATR AND HIGHER-LEVEL PROCESSING

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In an effort to model cortical networks and emulate higher-level brain function, especially in the recognition, classification, and learning of spatio-temporal signals of the kind occurring in natural and artificial settings, we have been investigating the dynamics of a new class of networks composed of parametrically coupled bifurcation processing elements. The spatio-temporal signals of particular interest to us are of the variety produced by sensor arrays in radar, sonar and ATR as result of relative motion between the sensor platform and the scattering object. The bifurcation processing elements in these networks are logistic maps representing netlets or neuronal assemblies of the cortex.

In the preceding quarterly report evidence was presented in support of the hypothesis that the basic functional unit in the cortex, the seat of higher-level brain function, maybe mathematically modeled by a bifurcation processing element: a parametrically driven noninvertible map on the unit interval such as the logistic map or the sine-circle map. Such simplifying abstraction seems to capture functional attributes of cortical units as seen in numerical simulations of a network of parametrically coupled bifurcation processing elements. Specifically, a bifurcation processing unit is functionally complex in that it can assume any of a number of qualitatively different functional modalities that include regular (fixed-point, periodic (period-m)) and irregular (intermittant, chaotic) activity and can bifurcate (rapidly switch) among them depending on the net input to the unit from other units. The network studied is shown to exhibit behavior remarkably similar to that seen in functional magnetic resonance imaging (fMRI) of brain function suggesting that it offers an efficient tool for modeling and studying cortical dynamics and higher-level brain function.

Under extrinsic dynamic input the network studied shows input-specific isolated clustering of activity analogous to the "hot-spots" of activity revealed by fMRI of brain activity of individuals subjected to sensory stimulus or engaged in mental activity associated with solving an assigned cognitive task.

Simulation results also predict that within the isolated active regions (hot-spots) neuronal groups assume complex temporal structures that describe fixed-point, periodic, quasi-periodic, intermittant, or chaotic orbits that serve apparently to further characterize the input stimulus. Unfortunately the temporal resolution of fMRI is not sufficient to reveal such temporal effects in actual observations. However other faster emergent functional brain imaging techniques such as magnetoencephalography (MEG) employing arrays of superconducting quantum interference devices (SQUIDS) or optical recoring techniques may be of help in testing this prediction. Positive verification of this prediction could have far reaching implications for brain modeling and help elucidate the role of such possible

temporal encoding in brain function furnishing thereby guidelines for the design of artificial intelligent systems.

Interestingly the network studied is found to exhibit the above behavior only when several salient or plausible attributes of thalamo-cortical organization and interaction were incorporated in it. This included predominance of local connections, nonlinear (activity-dependent) coupling between units, ability to accept extrinsic spatio-temporal input, and the gradual turning over of control of network dynamics from extrinsic (sensor driven) control to intrinsic (internal feedback) control.

We are continuing to examine the implications, predictive power, and applications of this class of networks which because of their ability to classify spatio-temporal input patterns are of interest in ATR and other areas such as speech processing. However most of the effort during the period of this report was directed to the issue of hardware implementation of networks of parametrically coupled logistic processing units that can furnish the speed needed in practical applications. To this end we concentrated on determining the plausibility of building logistic processing elements that can be used as building block in hardware implementations of parametrically coupled networks of logistic (bifurcation) processing units.

In previous work we have demonstrated that a programmable unijunction transistor (PUT) circuit with cosinusoidal modulation of the PUT's extinction voltage acts as a sine-circle map which exhibits bifurcation between distinct modalities and route to chaos. During the period of this report we attempted to answer the following question:

Can we obtain a spiking oscillator based on the PUT for which the logistic map emerges as the relationship between consecutive spikes? If this is possible, which modifications must be made in the original circuit (i.e., the circuit that implements the sine-circle map bifurcating processing element) in order to obtain this new dynamical behavior?

To date the work performed shows that by using the same kind of circuit employed for the earlier implementation of the sine-circle map bifurcating processing element as well as by appropriately changing the waveform of the periodic signal that is used to drive the PUT, the logistic recursion can, in fact, be obtained. This finding is being examined further because it seems to suggest that the PUT circuit with periodic modulation of extinction voltage may be useful for producing arbitrary maps on the interval and thus bifurcation processing elements with arbitrary desired properties by merely altering the shape of the periodic modulation waveform. If confirmed this finding could be important for dynamical computing employing timing or phase as variable and in encryption, secure communications and secure transponders.

Also during this period N. Farhat (PI) participated in the following meetings:

<u>1997 Annual Meeting of the Optical Society of America (OSA'97)</u>

where he presented two papers:

1. "Neuroholography: a Possible Link Between Holography and Cortical Information Processing."

2. "Biomorphic Networks for Invariant Feature Extraction."

He also participated in the:

<u>1997 International Symposium on Nonlinear Theory and Applications (NOLTA'97)</u>

by presenting a paper entitled:

"Dynamical Networks with Bifrucation Processing Elements." The paper was published in the Symposium proceeding. (copy attached).

Also during this period past work done under this grant was referred to in a special news report in Science under the title "A Subtler Silicon Cell for Neural Networks." (copy attached).

1997 International Symposium on Nonlinear
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DYNAMICAL NETWORKS WITH BIFURCATION PROCESSING ELEMENT

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Abstract: We introduce the concept of parametrically and nonlinearly coupled network of bifurcation processing elements that can be driven by static or dynamic input patterns. The network is biologically inspired, computes with all three-types of attractors and offers a unique tool for the modeling and study of cortical networks and higher-level brain function.

1. Introduction: There is considerable evidence that the basic functional unit for higher-level processing in the cortex is the *netlet* or *neuronal assembly (pool or group)* [1]-[10]. This evidence includes extensive analytical and modeling work of netlets carried out independently by several groups in the past. Nearly all that body of work points to the possibility that netlet dynamics, may be adequately described by the discrete time evolution of the activity A(n), which is the percentage of neurons in the netlet active at time n. Plots of A(n+1) vs. A(n) obtained under a range of circumstances and assumptions are found to invariably resemble a distorted version of the quadratic or logistic map, a nonlinear iterative map on the unit interval that exhibits complex orbits depending on the value of a nonlinearity (control or bifurcation) parameter [11]. The similarity between the netlet's return map A(n+1) vs. A(n) and that of the logistic map has also been noted by Harth [10] who also mentions that complex and unpredictable sequences A(n) were observed in some of their early simulations of netlets suggesting that certain regions of the netlet's parameter space can lead to observation of chaos in addition to the periodic and fixed point modalities they usually observed.

In light of this evidence we have conjectured that cortical networks can be modeled and numerically studied in an efficient way by means of *parametrically* coupled populations of logistic processing elements [12]. To test this conjecture we have studied the dynamics of such a network when it is subjected to dynamic input: external stimulus patterns that changed in time. The networks we study differ from coupled map lattices (CMLs), [13]-[14], in several ways: (a) The networks described here employ parametric rather than the diffuse coupling used in CMLs, (b) The coupling is nonlinear representing the possibility that the interaction between cortical netlets can depend on the activity of the netlets and on the number of active fibers connecting one netlet to another, (c) Parametrically coupled logistic nets (PCLNs) can be externally driven by dynamic or static patterns, or by composite patterns that are partially time varying and partially stationary, (d) In the PCLN, control over network dynamics is gradually handed over from initially entirely extrinsic control to eventually entirely intrinsic control. This gradual transfer of control over network dynamics from extrinsic to intrinsic is biologically plausible and is inspired by the remarkable biophysical observation made by Freeman and coworkers [15] regarding gradual disappearance of the trace of a sensory stimulus applied to the olfactory bulb of rabbit as it was followed deeper in the sensory cortex where it was found to eventually vanish in a sea of intrinsically dominated activity. Similar behavior has apparently been observed by Freeman's group in other sensory modalities.

The preceding remarks suggest that networks of parametrically coupled logistic maps offer an effective way to study the functional complexity of cortical networks in order to understand the way they perform higher-level functions. Such higher-level functions are beyond the capabilities of present day sigmoidal networks, and incorporating them in artificial network offers a way for increasing their processing power and for widening their scope of application.

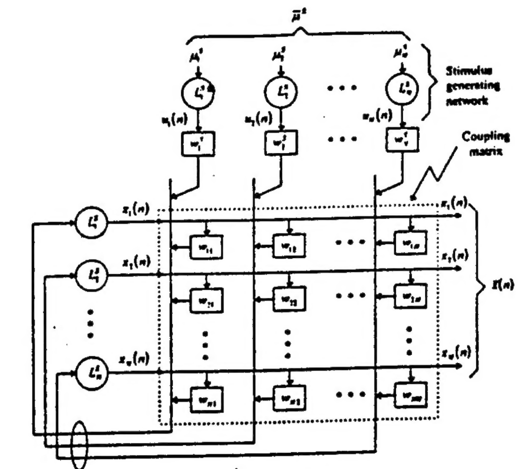
2. The Network: The network studied is shown in Fig. 1. It consists of a one-

dimensional array of N parametrically coupled logistic maps. Parametric coupling means the nonlinearity, (control or bifurcation parameter) μ_i of the i-th map is not fixed but is modulated in time. In the network, μ_i is modulated by both extrinsic and intrinsic influences according to

$$\mu_i(n) = \epsilon(n) g_i^S(n) + \frac{1 - \epsilon(n)}{2N_i} \sum_{j=i-N_i}^{i+N_i} g_{ij}(n), \qquad (1)$$

$$\epsilon(n) = \epsilon_o \exp(-\alpha n)$$

In eq. (1) i = 1,2,...N, the first term represents the extrinsic (sensory) input to the i-th logistic processing element or cell, the second term represents the net intrinsic input to the i-th cell through feedback from all other cells connected to it, n is discrete integer time, $2N_i$ is the number of logistic cells connected to the i-th cell i.e. the number of cells falling within a "connection radius R_C" that is taken to be identical for all cells, $g_i^S(n) = 4(u_i(n))^{w_i}$ is the extrinsic (sensory) input to the i-th cell with state variable $u_i(n) \in [0,1]$ being produced in the simulation conveniently by a sensory logistic map according to: $u_i(n+1) = \mu_i^S u_i(n)(1 - u_i(n))$ with $u_i(0) = 0.5$ and μ_i^S being a fixed control parameter of the i-th stimulus generating logistic map. Selecting μ_i^S in [0,4] enables the production of a wide range of stationary, periodic (period-m) or chaotic patterns $u_i(n)$ or any desired combination of such patterns on i depending on the values one selects for μ_i^S. Thus by adjusting the control vector $\overline{\mu}^S$ of the N stimulus generating logistic cells, a wide variety of spatio-temporal driving signals can be generated and applied to the network. The coupling factor w_i ranges between 0 and ∞. For example $w_i = 0$ produces $g_i^S(n) = 4$ which means the extrinsic contribution when added to the intrinsic one tends to make $\mu_i(n)$ high with the result that the i-th processing cell would tend to be chaotic. On the other hand $w_i = \infty$ yields



$$\mu_i(n) = \epsilon(n) w_i^s(u_i) + \frac{1-\epsilon(n)}{2N_i} \sum_{j=i-N_i}^{i+N_i} w_{ij}(x_j),$$

$$\epsilon(n) = \epsilon_o \exp(-\alpha n),$$

where ϵ_o is in $[0,1]$ and $\alpha \geq 0$ is positive real number.

w_i^s and w_{ij} are nonlinear activity dependent coupling functions with two possible forms each:

$$w_i^s = \begin{cases} g_i^s(u_i) = 4[u_i(n)]^{c_i^s} \\ B_i^s(u_i) = \text{quantized version of } g_i^s(u_i)\ (N_b \text{ levels}) \end{cases}$$

$$w_{ij} = \begin{cases} g_{ij}(x_i) = 4[x_i(n)]^{c_{ij}} \\ B_{ij}(x_i) = \text{quantized version of } g_{ij}(x_i)\ (N_b \text{ levels}) \end{cases}$$

Fig. 1. Parametrically coupled logistic network (PCLN) consisting of N bifurcation (logistic) processing elements or cells. The network employs: (a) novel biologically plausible nonlinear (activity) dependent coupling functions between cells each representing a netlet and (b) a biologically plausible gradual transfer of control over network dynamics from initially totally extrinsic (sensory) control to totally intrinsic control. The network can be driven externally by spatio-temporal inputs provided by the stimulus generating network that employs an array of uncoupled logistic maps to conveniently produce a variety of static, time-periodic, chaotic, or composite signals made of any mix of these three-types of signals. The quantized versions of the coupling functions used to study the coarse-grain dynamics of the PCLN (not discussed here).

$g_i^s(n) = 0$, because the state variable u_i of the logistic map is in [0,1]. This means that small values of w_i introduce disorder while larger values introduce inhibition. Similarly, the quantity $g_{ij}(n)$ in eq. (1) represents the input from the j-th cell to the i-th cell; it has a form similar to $g_i^s(n)$, namely $g_{ij}(n) = 4[X_j(n)]^{C_{ij}}$ with c_{ij} being in $[0,\infty]$ and $X_j(n)$ is the state variable of the j-th logistic processing cell of the network governed by: $X_j(n+1) = \mu_j(n)\left(1 - X_j(n)\right)$ where $\mu_i(n)$ is given by eq. (1) and $X_j(n)$ is also in [0,1]. Note the nonlinear dependence of $g_i^s(n)$ on $u_i(n)$ and of $g_{ij}(n)$ on $X_j(n)$ serves two purposes. One, it confines their combined contribution to $\mu_i(n)$ to the allowable range [0,4], and second, the values of w_i and C_{ij} provide control over the level of excitation/disorder on the one hand or inhibition on the other, that are injected into the dynamics of the i-th cell, and hence into the network as a whole, by the i-th sensory cell or by the j-th processing cell respectively. The parameter α in eq. (1) is a positive real constants whose value determines the speed with which control over the dynamic of the network is handed over from initially entirely extrinsic control to eventually and entirely intrinsic control. A value of $\epsilon_o = 1$ means that initially the dynamics of the network are totally controlled by the extrinsic (sensory) pattern and $\alpha = 0$ means there is no fading of the effect of extrinsic input.

The behavior of the PCLN was numerically studied under a variety of conditions and parameter values and extremely rich behavior was observed. Particularly interesting was the behavior when local connectivity was used where $N_i << N$ to reflect presumably the dominance of local inter-connection between netlets of the cortex. When self-connection of cells was allowed and the following parameters were used: R_c randomly selected in [0,1], $\epsilon_o = 1$, $\alpha = 0.1$, $w_i = 0.5$, and random coupling coefficients i.e., C_{ij} randomly and uniformly selected in [a,b], and random initial state vector $\overline{X}(0)$ i.e. $X_i(0)$ randomly and uniformly selected in [0,1], the network exhibited isolated clusters of activity for values of the constants a ranging in [0,0.3] and b=3 which furnished a mix of chaos and order inducing coupling functions. The form of isolated clustering, and the orbits of cells within clusters, were stimulus specific and independent of initial state of the network, as desired. The clustering was relatively rapid occurring usually within the first 100 iterations depending on the value of α. Cell orbits of different type i.e., fixed-point, period-m, and chaotic can coexist within a cluster and often the period-m orbits of cells within well separated clusters were not only phase-locked but synchronized. This latter behavior conforms with synchronized oscillations of local field potentials observed by several workers in the brain of cat and monkey and with Eckhorn's modeling of that behavior in networks of spiking neurons [16]-[21]. Most interesting is the isolated clustering which is analogous to the isolated clusters of brain activity seen in functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) images of subjects subjected to sensory stimulus or when performing an assigned cognitive or motor task.

The conceptual similarity of the isolated clustering behavior in PCLNs and the clustering of brain activity seen in fMRI and PET raises an interesting scientific question. If PCLNs are valid models of cortical nets then the clusters of brain activity seen in fMRI and PET should also exhibit analogous temporal activity. Unfortunately the time resolution of fMRI and PET at present is too coarse to discern any temporal activity within the clusters that light-up because both measure the change in blood flow to active brain regions. An increasing number of studies employing PET and fMRI show however that different sensory stimuli or cognitive tasks can "light-up" the same brain spot. This strongly suggests a role for temporal encoding to enable differentiation. It would be interesting to see if future technological advances in functional brain imaging could provide the needed temporal resolution to verify the prediction of the PCLN.

3. **Conclusion:** The generally rich behavior we observe with PCLNs including the remarkable specific behaviors described above have no parallel in sigmoidal neural network, and apparently also in coupled map lattices and cellular automata. Therefore we believe that the

use of PCLNs to model cortical networks and higher-level brain functions provide a unique tool for the development of intelligent systems that can operate in a natural environment where time varying signatures are the norm and not the exception.

4. Acknowledgement: I wish to thank G-H Lee for writing the *Windows* program on which the simulations referred to were carried out. This research was supported by the Office of Naval Research under grant no. N00014-94-1-0931.

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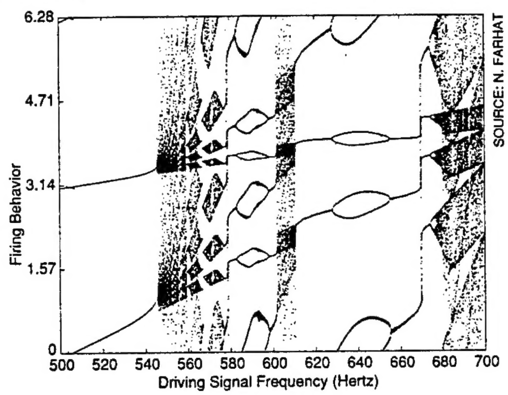
A Subtler Silicon Cell for Neural Networks

Nature is the model for artificial neural networks. These networks of processors—either real or simulated on a conventional computer—"learn" from experience by adjusting the strength of their connections, much like networks of real neurons. Small neural nets have become commonplace, doing tasks such as predicting how stock prices may fluctuate and recognizing handwritten characters. But Nabil Farhat of the University of Pennsylvania, Philadelphia, thinks he can build a better neural net by making its constituent neurons even closer to biology.

Neural nets traditionally consist of so-called sigmoidal neurons, circuits that add up incoming signals until they reach a fixed threshold and then fire themselves. Farhat's so-called bifurcation neurons, in contrast, switch between different modes of operation—between regular and chaotic firing, for example—depending on subtler factors. These include not just the value of a particular train of incoming signals, but also the interaction between many incoming signals and the neuron's recent history. So far, Farhat has made only single neurons, and he hasn't linked them together into a complete network. But his latest simulations suggest, he says, that they could yield neural nets with more lifelike behavior than has been seen in networks to date, such as the ability to see, recognize, and even react to the world in real time.



Nervous behavior. The bifurcation neuron switches among many different firing modes, depending on the frequency of the signal it receives.

Whether he will succeed is still an open question, says Daniel Collobert, a neural net expert at France Telecom. But he notes that Farhat's bifurcating neuron provides a level of behavioral complexity "that [artificial] neural networks could not previously [show], and I guess never will, because of the functional simplicity of [their] neurons."

The neurons in traditional nets sacrifice important information, because they know only how many spikes reached them in a given period, but not when each spike arrived. To an ordinary neuron, the periodic signal 110110110 (where a 1 is a spike) would be exactly the same as 101101101.

Yet real neuronal nets, in the brain, capture this timing information. A neuron fires because incoming signals cumulatively depolarize the excitable membrane of the neuron's output device, the axon. Afterward, there follows a period when the membrane cannot respond at all to an incoming signal, which gives way to another slow buildup. A pulse arriving immediately after firing will have a completely different effect on the output of the neuron from one that arrives immediately before.

Real neurons also respond differently to signals when they are correlated than when they arrive separately. Farhat explains that signals arriving simultaneously through different dendrites produce a periodic modulation of the neuron's electrically excitable membrane, just as two beams of light from the same source produce a periodic pattern of light and dark patches when they interfere with each other. The oscillation modulates the neuron's response to later inputs.

Conventional digital circuitry, with its arrays of on-off switches, can't efficiently mimic this kind of behavior. So Farhat has been combining resistors, capacitors, and other components into so-called analog circuits, which can adopt any intermediate state between "on" and "off." One proof-of-principle design incorporated two capacitors, which charge up in parallel as incoming signals build up. Eventually, one capacitor "breaks down," allowing current to flow, which switches on a light-emitting diode. The diode discharges both capacitors, reversing the breakdown and allowing the charging to begin again. This behavior makes the circuit time-sensitive: Signals arriving when the capacitors have just been discharged have a different effect from signals arriving earlier or later.

The latest incarnations of Farhat's neurons display more complex behavior (see diagram). When many neural inputs (spike trains) arrive at the same time, they interact to generate an electrical oscillation, which affects the neuron's firing. Small changes in the frequency of this oscillation, caused by varying input signals, produce huge shifts in the output behavior. For instance, oscillation frequencies below about 550 hertz produce periodic firing with two spikes per cycle. Just above this frequency, the output rapidly changes to chaotic firing.

Farhat and his colleagues are now planning to link such neurons into a full array using optical signals, which should allow them to create the dense thicket of interconnections needed for a large neural net. In a paper to be published in the *Journal of Intelligent and Robotic Systems* early next year, Farhat describes a computer simulation that offers a glimpse of how such a network would behave. The bifurcation neurons seem to form "netlets"—subsets of the neurons that work together. In an even more recent simulation, Farhat found that the netlets formed a kind of neuroanatomy, with different clusters of netlets responding to stimuli from different sources in the environment. "That's exactly the same as people observe when they look at functional MRI [magnetic resonance imaging] and PET [positron emission tomography] scans of the brain," Farhat says. "Depending on the inputs, the stimulus from the outside, or the cognitive task that the person is engaged in, we see different parts of the brain firing." It's that kind of complexity, Farhat thinks, that could make his networks of bifurcation neurons capable of simple abilities that we take for granted.

–Sunny Bains

Sunny Bains is a science and engineering writer in Edinburgh, U.K.

mimic some aspects of the brain in so-called neural nets, networks of "processors" linked by "synapses"—connections that strengthen or weaken depending on activity, enabling the net to learn from experience. But these neural nets generally aren't real physical devices—instead, they are simulated ones, running as software on conventional computers. What's more, their neurons are, with few exceptions (see sidebar), generally much simplified versions of the real thing. Neuromorphics, on the other hand, is an effort to capture some of the richness of actual neurons in hardware—transistors, capacitors, and resistors, all fabricated onto silicon chips—in what is called analog VLSI, or simply AVLSI.

Besides allowing transistors to operate at many different voltage levels, neuromorphic engineers are designing them to serve as both calculation and memory elements. Work by Lance Glasser at the Massachusetts Institute of Technology, and by Mead and his team at Caltech, has led to the design of a new type of transistor, the floating gate transistor, which

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